Modeling and forecasting inflation in Burundi using ARIMA models

THABANI NYONI

University of Zimbabwe

25 February 2019

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Nyoni, Thabani

Department of Economics

University of Zimbabwe

Harare, Zimbabwe

Email: nyonithabani35@gmail.com

ABSTRACT

This research uses annual time series data on inflation rates in Burundi from 1966 to 2017, to model and forecast inflation using ARIMA models. Diagnostic tests indicate that B is I(1). The study presents the ARIMA (0, 1, 1). The diagnostic tests further imply that the presented optimal ARIMA (0, 1, 1) model is stable and acceptable for predicting inflation in Burundi. The results of the study apparently show that B will be approximately 9.4% by 2020. Policy makers, particulary, monetary authorities in Burundi are expected to tighten Burundi's monetary policy in order to restore price stability.

Key Words: Burundi, Forecasting, Inflation

JEL Codes: C53, E31, E37, E47

INTRODUCTION

Inflation is the sustained increase in the general level of prices and services over time (Blanchard, 2000). The negative effects of inflation are widely recognized (Fenira, 2014). Inflation is one of the central terms in macroeconomics (Enke & Mehdiyev, 2014) as it harms the stability of the acquisition power of the national currency, affects economic growth because investment projects become riskier, distorts consuming and saving decisions, causes unequal income distribution and also results in difficulties in financial intervention (Hurtado *et al*, 2013).

As the prediction of accurate inflation rates is a key component for setting the country's monetary policy, it is especially important for central banks to obtain precise values (Mcnelis & Mcadam, 2004). To prevent the aforementioned undesirable outcomes of price instability, central banks require proper understanding of the future path of inflation to anchor expectations and ensure policy credibility; the key aspects of an effective monetary policy transmission mechanism (King, 2005). Inflation forecasts and projections are also often at the heart of economic policy decision-making, as is the case for monetary policy, which in most industrialized economies is mandated to maintain price stability over the medium term (Buelens, 2012). Economic agents, private and public alike; monitor closely the evolution of prices in the economy, in order to make decisions that allow them to optimize the use of their resources (Hector & Valle, 2002). Decision-makers hence need to have a view of the likely future path of inflation when taking measures that are necessary to reach their objective (Buelens, 2012). To avoid adjusting policy and models by not using an inflation rate prediction can result in imprecise investment and saving decisions, potentially leading to economic instability (Enke &

Mehdiyev, 2014). In this study, we seek to model and forecast inflation in Burundi using ARIMA models.

LITERATURE REVIEW

Meyler *et al* (1998) forecasted Irish inflation using ARIMA models with quarterly data ranging over the period 1976 to 1998 and illustrated some practical issues in ARIMA time series forecasting. Nyoni (2018) studied inflation in Zimbabwe using GARCH models with a data set ranging over the period July 2009 to July 2018 and established that there is evidence of volatility persistence for Zimbabwe's monthly inflation data. Nyoni (2018) modeled inflation in Kenya using ARIMA and GARCH models and relied on annual time series data over the period 1960 – 2017 and found out that the ARIMA (2, 2, 1) model, the ARIMA (1, 2, 0) model and the AR (1) – GARCH (1, 1) model are good models that can be used to forecast inflation in Kenya. Sarangi *et al* (2018) analyzed the consumer price index using Neural Network models with 159 data points and revealed that ANNs are better methods of forecasting CPI in India. Nyoni & Nathaniel (2019), based on ARMA, ARIMA and GARCH models; studied inflation in Nigeria using time series data on inflation rates from 1960 to 2016 and found out that the ARMA (1, 0, 2) model is the best model for forecasting inflation rates in Nigeria.

MATERIALS & METHODS

One of the methods that are commonly used for forecasting time series data is the Autoregressive Integrated Moving Average (ARIMA) (Box & Jenkins, 1976; Brocwell & Davis, 2002; Chatfield, 2004; Wei, 2006; Cryer & Chan, 2008). For the purpose of forecasting inflation rate in Burundi, ARIMA models were specified and estimated. If the sequence $\Delta^d B_t$ satisfies an ARMA (p, q) process; then the sequence of B_t also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d B_t = \sum_{i=1}^{p} \beta_i \Delta^d B_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [1]$$

which we can also re – write as:

$$\Delta^d B_t = \sum_{i=1}^{p} \beta_i \Delta^d L^i B_t + \sum_{i=1}^{q} \alpha_i L^i \mu_t + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [2]$$

where Δ is the difference operator, vector $\beta \in \mathbb{R}^p$ and $\alpha \in \mathbb{R}^q$.

The Box – Jenkins Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018).

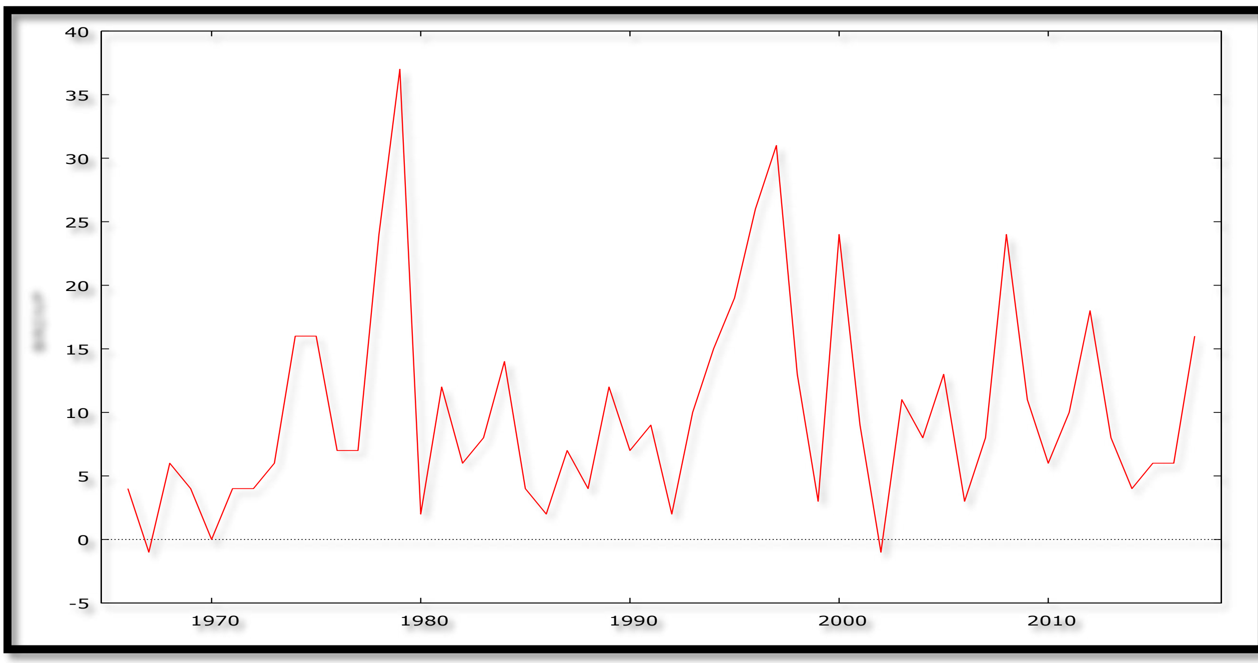
Data Collection

This study is based on a data set of annual rates of inflation in Burundi (BRINF or simply B) ranging over the period 1966 – 2017. All the data was adapted from the World Bank.

Diagnostic Tests & Model Evaluation

Stationarity Tests: Graphical Analysis

Figure 1



The Correlogram in Levels

Autocorrelation function for BRINF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 1

LAG	ACF	PACF	Q-stat. [p-value]
1	0.2688 *	0.2688 *	3.9774 [0.046]
2	-0.0319	-0.1122	4.0346 [0.133]
3	0.1406	0.1969	5.1680 [0.160]
4	0.1163	0.0145	5.9596 [0.202]

5	0.0169	0.0066	5.9767 [0.308]
6	-0.2098	-0.2544 *	8.6624 [0.193]
7	-0.2108	-0.1137	11.4348 [0.121]
8	-0.1685	-0.1597	13.2474 [0.104]
9	-0.2340 *	-0.1431	16.8217 [0.052]
10	-0.1385	0.0052	18.1049 [0.053]

The ADF Test in Levels

Table 2: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
B	-5.298022	0.0000	-3.565430	@1%	Stationary
			-2.919952	@5%	Stationary
			-2.597905	@10%	Stationary

Table 3: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
B	-5.316	0.003	-4.148465	@1%	Stationary
			-3.500495	@5%	Stationary
			-3.179617	@10%	Stationary

Table 4: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
B	-1.180820	0.2140	-2.613010	@1%	Non-stationary
			-1.947665	@5%	Non-stationary
			-1.612573	@10%	Non-stationary

Although tables 2 and 3 show that B is stationary in levels, figure 1, table 1 and table point the opposite. Therefore, the researcher had to carry out further tests to verify the stationarity of B.

The Correlogram (at 1st Differences)

Autocorrelation function for d_BRINF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 5

LAG	ACF	PACF	Q-stat. [p-value]
1	-0.2934 **	-0.2934 **	4.6522 [0.031]
2	-0.3198 **	-0.4441 ***	10.2944 [0.006]
3	0.1366	-0.1761	11.3448 [0.010]
4	0.0418	-0.1508	11.4453 [0.022]

5	0.0804	0.0854	11.8256 [0.037]
6	-0.1473	-0.0914	13.1284 [0.041]
7	-0.0227	-0.0501	13.1602 [0.068]
8	0.0813	-0.0647	13.5760 [0.094]
9	-0.1280	-0.2100	14.6311 [0.102]
10	0.0361	-0.1408	14.7170 [0.143]

ADF Test in 1st Differences

Table 6: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
B	-8.838437	0.0000	-3.571310	@1%	Stationary
			-2.922449	@5%	Stationary
			-2.599224	@10%	Stationary

Table 7: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
B	-8.745482	0.0000	-4.156734	@1%	Stationary
			-3.504330	@5%	Stationary
			-3.181826	@10%	Stationary

Table 8: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
B	-8.926375	0.0000	-2.613010	@1%	Stationary
			-1.947665	@5%	Stationary
			-1.612573	@10%	Stationary

Tables 6 – 8 reveal that B became stationary after taking first differences and is thus an I (1) variable.

Evaluation of ARIMA models (without a constant)

Table 9

Model	AIC	ME	MAE	RMSE
ARIMA (1, 1, 0)	376.489	0.24685	7.1029	9.321
ARIMA (0, 1, 1)	**365.8733**	0.58095	6.3899	8.3485
ARIMA (2, 1, 1)	366.6388	0.34849	6.4916	8.1039
ARIMA (2, 1, 0)	367.2612	0.28225	6.6462	8.3266

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018). The study will only consider the AIC as the criteria for choosing the best model for predicting inflation in Burundi. Hence, the ARIMA (0, 1, 1) model is selected finally.

Residual & Stability Tests

ADF Tests of the Residuals of the ARIMA (0, 1, 1) Model

Table 10: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-5.456282	0.0000	-3.568308	@1%	Stationary
			-2.921175	@5%	Stationary
			-2.598551	@10%	Stationary

Table 11: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-5.399673	0.0003	-4.152511	@1%	Stationary
			-3.502373	@5%	Stationary
			-3.180699	@10%	Stationary

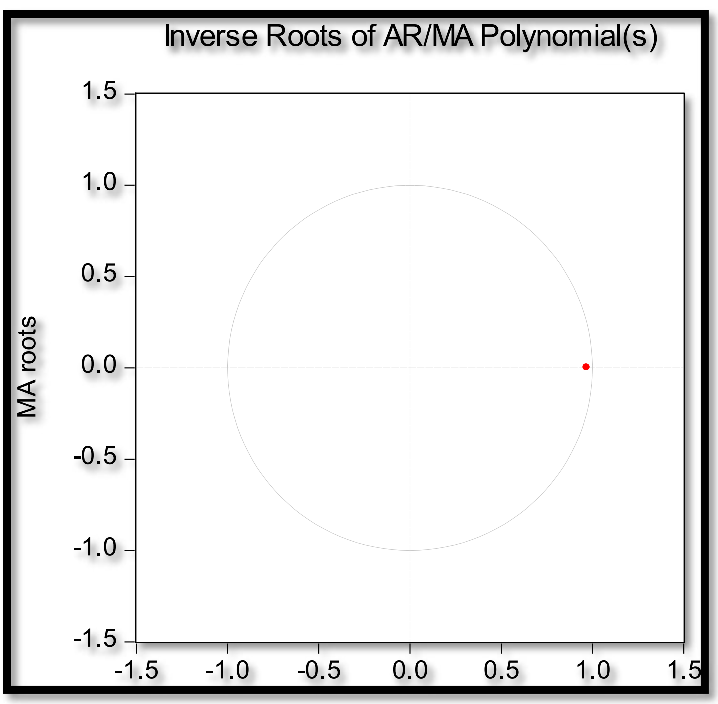
Table 12: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-5.511921	0.0000	-2.612033	@1%	Stationary
			-1.947520	@5%	Stationary
			-1.612650	@10%	Stationary

Tables 10, 11 and 12 show that the residuals of the ARIMA (1, 1, 2) model are stationary and hence the ARIMA (0, 1, 1) model is suitable for forecasting inflation in Burundi.

Stability Test of the ARIMA (0, 1, 1) Model

Figure 2



Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen ARIMA (0, 1, 1) model is stable and suitable for predicting inflation in Burundi over the period under study.

FINDINGS

Descriptive Statistics

Table 13

Description	Statistic
Mean	10.077
Median	8
Minimum	-1
Maximum	37
Standard deviation	8.1285
Skewness	1.28
Excess kurtosis	1.4829

As shown above, the mean is positive, i.e. 10.077%. The minimum is -1% and the maximum is 37%. The skewness is 1.28 and the most striking characteristic is that it is positive, indicating that the inflation series is positively skewed and non-symmetric. Excess kurtosis was found to be 1.4829; implying that the inflation series is not normally distributed.

Results Presentation[1]

Table 14

ARIMA (0, 1, 1) Model:

$$\Delta B_{t-1} = -0.776344\mu_{t-1} \ldots \ldots \ldots \ldots \ldots [3]$$

P: (0.0000)

S. E: (0.0919739)

Variable	Coefficient	Standard Error	z	p-value
MA (1)	-0.776374	0.0919739	-8.441	0.0000***

Predicted Annual Inflation in Burundi

Table 15

Year	Prediction	Std. Error	95% Confidence Interval
2018	9.94	8.329	-6.39 - 26.26
2019	9.94	8.535	-6.79 - 26.66
2020	9.94	8.736	-7.19 - 27.06

[1] *The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively.*

2021	9.94	8.932	-7.57 - 27.44
2022	9.94	9.125	-7.95 - 27.82
2023	9.94	9.313	-8.32 - 28.19
2024	9.94	9.497	-8.68 - 28.55
2025	9.94	9.678	-9.03 - 28.90
2026	9.94	9.856	-9.38 - 29.25
2027	9.94	10.030	-9.72 - 29.59

Table 15, with a forecast range from 2018 – 2027; clearly show that inflation in Burundi is projected to be hovering around 9.94% in the next 10 years. This implies that there is need to control inflation in Burundi because our forecasts indicate that it is likely to be generally around 10% over the next decade. Now, 2 digit inflation figures are not healthy to the economy, hence the need to deal with the threat of inflation in Burundi.

CONCLUSION

The ARIMA model was employed to investigate annual inflation rates in Burundi from 1966 to 2017. The study planned to forecast inflation in Burundi for the upcoming period from 2018 to 2027 and the best fitting model was carefully selected based on the minimum AIC value. The ARIMA (0, 1, 1) model is stable and most suitable model to forecast inflation in Burundi for the next ten years. Based on the results, policy makers in Burundi should continue to engage proper economic policies in order to fight against persistent inflationary pressures in the economy. In this regard, the Banque de la Republique du Burundi (the central bank of Burundi) is encouraged to tighten its monetary policy in order to foster macroeconomic stability in the country.

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